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THE IMPACT OF COVID-19 ON EDUCATION IN LATIN AMERICA: LONG-RUN IMPLICATIONS FOR POVERTY AND INEQUALITY

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The shock of the COVID-19 pandemic affected the human capital formation of children and youths. As a consequence of this disruption, the pandemic is likely to imply permanent lower levels of human capital. This paper provides new evidence on the impact of COVID-19 and school closures on education in Latin America by exploiting harmonized microdata from a large set of national household surveys carried out in 2020, during the pandemic. In addition, the paper uses microsimulations to assess the potential effect of changes in human capital due to the COVID-19 crisis on future income distributions. The findings show that the pandemic is likely to have significant long-run consequences in terms of incomes and poverty if strong compensatory measures are not taken soon.

JEL Codes: O1, I31, I24

Keywords: COVID-19, education, poverty, inequality, incomes, Latin America

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1. INTRODUCTION

During 2020 and 2021, the COVID-19 pandemic affected the lives of everyone. To contain the spread of the disease, most governments imposed national lockdowns, travel restrictions, and social-distancing measures, including school closures. Latin America was not an exception. On average across countries, in 2020 and 2021 schools were closed for 269 days. Given that a typical school year in the region takes 189 days, school closures represented a disruption of 1.42 years. National education systems provided remote learning options and other tools to hamper the learning interruptions, but undoubtedly the process of human capital formation of children and youths was affected. Due to this disruption, the pandemic will likely imply permanent lower levels of human capital for many individuals, and therefore lower earnings (see the surveys in Blanden et al., 2023 and Moscoviz & Evans, 2022).¹ The magnitude of this impact on human capital formation will be contingent upon the age of the children and family socioeconomic background (Cunha et al., 2010; Cunha & Heckman, 2007), implying asymmetric effects on skills formation and, eventually, on inequality.

In this paper we provide new evidence on the impact of the COVID-19 pandemic and the associated school closures on school dropouts and educational losses in Latin America. We take advantage of microdata from national household surveys for 2020 that allows us to explore changes in school enrollment for 13 Latin American countries, which add up to 89 percent of the total population of the region and 87 percent of the school-age population. The countries included are: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Mexico, Paraguay, Peru and Uruguay. To estimate the change in school enrollment associated with the pandemic, we run regressions of the outcome of interest—an indicator of whether the individual is enrolled at school—on a linear time-trend from 2009 to 2019, a binary indicator for the year 2020, and a set of controls. To comprehend the influence of the pandemic more thoroughly—and the financial struggles experienced by families—on educational investment, we also consider private education enrollment, usually characterized by superior quality and elevated cost, as a dependent variable.

Our results show that in all countries enrollment rates in 2020 negatively deviate from the previous trend. On average, enrollment of children and young people aged 6–24 fell by around two percentage points. The decrease in enrollment in private education is also in this order of magnitude in absolute terms, but larger in relative terms because of the lower average baseline level. These results are in line with simulations that predict large long-run costs of the pandemic in terms of educational drop-out and decrease in average years of schooling (e.g., Azevedo et al., 2021; Neidhöfer et al., 2021). Moreover, the decline in private school enrollment indicates a substantial effect of the economic difficulties faced by families during the pandemic on educational investments.

¹Psacharopoulos et al. (2020) estimate that at the global level, the present value of a four-month school interruption implies an earnings loss of more than US\$10,000 over the course of a lifetime. Using a structural model matched to US data, Fuchs-Schündeln et al. (2022) find that earnings losses amount to about 1% over the lifetimes.

In the second part of the paper, we carry out some basic microsimulations to assess the potential effect of changes in human capital due to the COVID-19 crisis on future income distributions. Specifically, we simulate earnings assuming the COVID-19 pandemic affected human capital through two channels: a reduction in school days and an increase in dropouts. We find that the pandemic is likely to have significant long-term consequences in terms of incomes and poverty if strong compensatory measures are not taken soon.

The rest of the paper is organized as follows. In Section 2 we discuss the key features of the COVID-19 pandemic in Latin America along with the ensuing social distancing measures, stressing the scope of the school closures. In Section 3 we analyze the impact of the pandemic on enrollment at public and private schools taking advantage of a large set of harmonized national household surveys—including those collected in 2020—in 12 Latin American countries. In Section 4 we adopt the framework of Neidhöfer et al. (2021) to approximate months of instructional losses associated to the school closures during the crisis. In particular, we use an updated version of these calculations and compute them at the individual level by exploiting microdata from national household surveys. In Section 5 we carry out microsimulations to provide some rough estimates of the potential impact of the educational losses on future incomes, and on indicators of poverty and inequality in the region. We conclude in Section 6 with a discussion of the results and their implications.

2. COVID-19 AND SCHOOL CLOSURES

During the COVID-19 pandemic the well-being of children was challenged by several contemporaneous shocks potentially affecting their human capital persistently. The health crisis was accompanied by an economic crisis, and, on top of that, school closures had a direct effect on children's learning (see the reviews of the evidence by Hammerstein et al., 2021 and Werner & Woessmann, 2021). Particularly in Latin America, the impact of the pandemic on these three dimensions has been among the strongest worldwide. Indeed, considering all these dimensions—health crisis, economic downturn, and educational losses—Neidhöfer et al. (2021) predict through simulations a large drop in the likelihood of completing secondary education for current cohorts aged 15–19 in Latin America. Subsequent studies based on real-time information from surveys or administrative data on learning losses, disconnection from school, and drop-out rates in 2020 confirm that the pandemic had a significant negative short-term effect on education in all countries in the region (see the review of the real-time evidence included in Lustig et al., 2021).

While these estimates refer to the year 2020, the situation did not improve substantially in 2021. Although Latin American economies recovered slightly with respect to the previous year, a high number of infections still limited school openings and in person learning in most countries.² Table 1 shows the number of weeks that

²The debate on the efficacy of school closures as a measure to mitigate the spread of SARS-CoV-2 in the first and subsequent waves is still ongoing, although most of the evidence highlights that children play an important role in the community transmission of the virus due to a higher exposure in schools (see Pierce et al., 2022).

TABLE 1
SCHOOL CLOSURES AND COVID-19 INFECTIONS IN LATIN AMERICA, 2020 AND 2021

	Number of weeks with schools fully or partially closed in 2020 and 2021	Number of weeks in two regular academic years	Cumulative COVID-19 cases per 1000 inhabitants (December 31, 2021)	Cumulative COVID-19 deaths per 1000 inhabitants (December 31, 2021)
Argentina	82	88	124.0	2.6
Bolivia	82	87	50.7	1.7
Brazil	79	85	103.6	2.9
Chile	69	88	94.0	2.0
Colombia	77	86	100.6	2.5
Costa_Rica	82	88	111.0	1.4
Dominican Republic	55	73	38.2	0.4
Ecuador	85	91	30.7	1.2
El Salvador	80	85	18.7	0.6
Guatemala	83	89	34.4	0.9
Honduras	80	86	37.7	1.0
Mexico	78	85	30.6	2.3
Nicaragua	15	86	2.6	0.0
Panama	84	89	113.2	1.7
Paraguay	74	79	64.6	2.3
Peru	77	83	68.9	6.1
Uruguay	41	74	118.6	1.8
Venezuela	74	83	15.5	0.2

Source: Own calculations based on administrative data.

schools were fully or partially closed during the period 2020–2021 in each country, the regular weeks of school that children would have had without the pandemic in these 2 years, as well as the number of cumulative COVID-19 cases and deaths at the end of 2021. In most countries, the share of weeks with closed schools exceeds 90 percent of the instructional time in the two academic years. The average across all countries is 85 percent. Interestingly, although surely the epidemiological situation was the main driver of the decision to close schools at the national level, there seems to be no clear association between the relative number of cases and deaths and the number of weeks with closed schools across countries.

The closure of schools was accompanied by the efforts of national education systems to provide remote learning options and tools to hamper the learning interruptions. In most countries, some sort of education was provided via TV, radio, or printed copies sent to the families. Furthermore, as in many other sectors, the use of online resources was expanded substantially. Figure 1 summarizes for each Latin American country the provision of offline and online remote learning resources during the pandemic. The axes represent indexes of offline and online learning drawn from Neidhöfer et al. (2021). The offline learning index measures the incidence of strategies channeled through TV, cellphone, radio and printed copies, whereas the online learning index captures the preparedness of schools, teachers, and the education system to provide online learning resources. The graph suggests

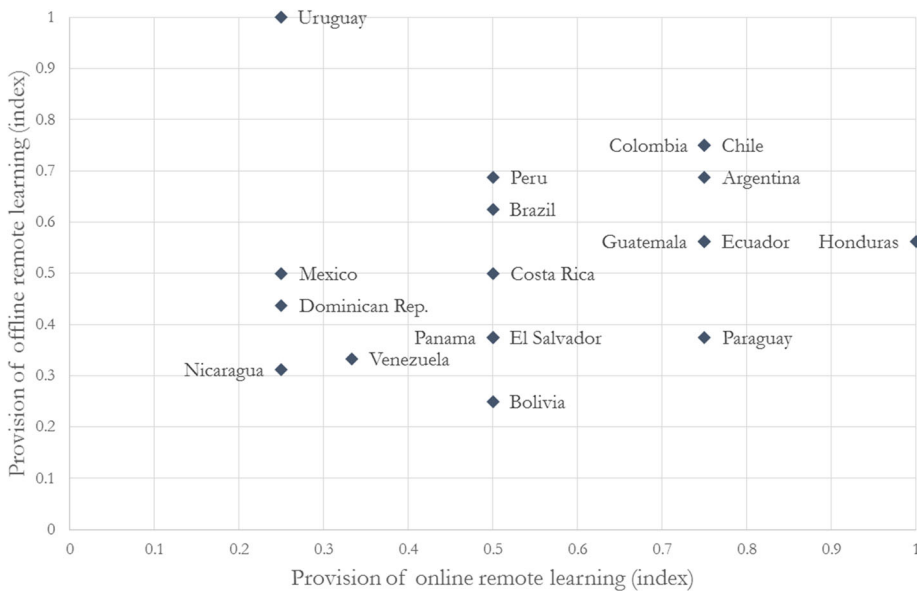


Figure 1. Provision of Online and Offline Remote Learning in 2020.
Source: Data from Neidhöfer et al. (2021).

a positive correlation between the provision of offline and online resources across countries.

3. THE IMPACT ON ENROLLMENT

In this section we exploit harmonized microdata from national household surveys (NHS) to explore changes in the patterns of school enrollment in a large set of Latin American countries. In particular, we make use of microdata from national surveys carried out in 2020, which allows us to study the impact of the pandemic on schooling.

We assess changes in enrollment in all education levels by comparing the year 2020 with around 10 years preceding the pandemic and quantifying by how much enrollment rates in 2020 are deviating from the previous trend. This analysis sheds light on educational dropouts occurring due to the pandemic. Furthermore, we analyze changes in educational investments during the pandemic by estimating changes in the likelihood of enrollment in private education during 2020.

3.1. Methodology and Data

The analysis of this section is based on microdata from the official national household surveys of the Latin American countries for which cross-sections spanning the period 2010–2020 are available: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Mexico, Peru, and

Paraguay.³ For each country in our sample, we pool the available survey waves from 2010 (2009 in some countries) to 2020 and restrict the sample to include individuals aged 6–24. To estimate the change in enrollment in 2020, we run a regression of the outcome of interest—whether the child is enrolled at school or not—on a linear time-trend and a dummy variable indicating that the observation refers to the year 2020. Formally, we estimate the following equation:

$$(3.1) \quad Y_{it} = \alpha + \beta A2020_{it} + \tau_t + \gamma X_{it} + \epsilon_{it}$$

where Y indicates whether individual i surveyed in year t is enrolled at school,⁴ $A2020$ is a dummy variable that takes the value 1 for the year 2020, τ stands for a linear time trend, X is a vector including control variables to abstract from potential changes in sample composition, namely age, sex, urban or rural area of residency, and parental education, and ϵ is the error term. The coefficient of interest is β , which indicates the deviation, in percentage points, of enrollment rates in the year 2020 with respect to the overall trend in enrollment rates, conditional on all the above-mentioned controls. We estimate these regressions for each country separately, as well as for the pooled sample including all countries and including country fixed effects.

We consider both enrollment and net enrollment in primary, secondary or tertiary education. While enrollment takes into account all of students enrolled in a particular level of education regardless of age, net enrollment focuses on the appropriate age group for each educational level, excluding students who are above or below the expected age. Also, we analyze enrollment at private schools—as opposed to public schools—conditional on being enrolled.

3.2. Change in Educational Enrollment

Figure 2 summarizes the results from estimating Equation (3.1) for the pooled sample of 12 countries, considering enrollment at the educational system without distinguishing educational levels. The figure shows by how much the estimated enrollment in 2020 differs from the trend in enrollment rates of the previous decade for the entire region.⁵ Since we do not have surveys for each year in each country, we group survey years such that in every time-period every country is included. The point estimates show the (population-unweighted) average estimate across all countries, controlling for sex, age, urban or rural place of residence, and

³Surveys were processed following the protocol of the Socioeconomic Database for Latin America and the Caribbean (SED-LAC), a joint project between CEDLAS at the Universidad Nacional de La Plata and the World Bank (SED-LAC, 2021). Table A1 in the Appendix shows basic information on the Latin American national household surveys used in this paper.

⁴For simplicity, we employ the terms “enrollment” and “attendance” interchangeably. In household surveys, a common inquiry seeks to determine if the child is currently enrolled in school, which is interpreted as active participation in the educational process. This involvement may encompass physical attendance during a standard academic year or engagement in remote learning in instances of school closures, such as those experienced during the pandemic.

⁵In this analysis we normalize the survey design weights for each country in each year to avoid having different sample sizes and sample weights influence the estimated coefficient.

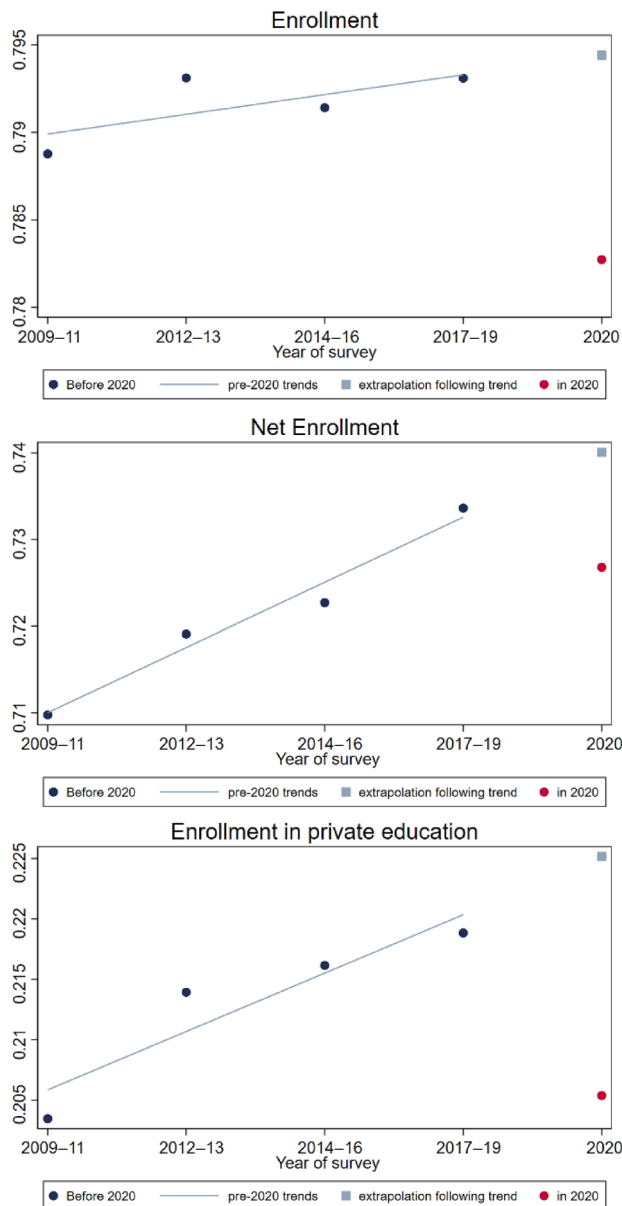


Figure 2. Changes in Trend With Respect to the Expected Enrollment Rates in 2020; Latin America (Pooled Sample).

Notes: Pooled Sample with Normalized Survey Design Weights of all Latin American Countries Included in the Analysis. Sample Includes Individuals Aged 6–24. Dependent Variable Indicated in the Title of Each Graph. The Dots from 2009 to 2019 and in 2020 Show Linear Predictions of Enrollment in Each Period. Regressions Include Control Variables for Age, Sex, Urban or Rural Place of Residence, and Parental Education. The Counterfactual Estimate for the Enrollment Rates in 2020 is Computed by Extrapolation, Following the Trend of the Previous Periods. The Line Shows the Linear Fit of the Observations from 2009 to 2019.

Source: National Household Surveys, 2009–2020. Own Estimates

parental education. The counterfactual estimate for the enrollment rates in 2020 is computed by extrapolation, following the trend of the previous periods. From Figure 2 it is clear that the actual enrollment rates in 2020 are substantially lower than the counterfactual.

Table 2 shows the coefficient estimates of the dummy for the year 2020—that is, the estimated β in Equation (3.1)—for each country, controlling for the characteristics mentioned above. The size of the coefficient indicates the deviation in percentage points from the overall trend, conditional on the included controls. The last row shows the average value of the dependent variable over the years—that is, 2009–2020. Panel A of the table shows the results for enrollment, Panel B for net enrollment, Panel C for enrollment at private schools.

In all countries enrollment rates negatively deviate from the trend in 2020. In most countries, this change is statistically significant. On average, measured over the 12 Latin American countries in our sample, enrollment of children and young people between 6 and 24 years old fell by around two percentage points. The decrease in net enrollment and enrollment at private schools is also in this order of magnitude in absolute terms, but higher in relative terms because of the lower average baseline level. A decrease in enrollment by two percentage points means that a large number of Latin American children and young people—around three million—dropped out of school or did not enroll in the higher track due to the pandemic in 2020. The strongest decline in enrollment is found in Chile and Peru—around 5 percentage points.

Figure 3 shows the results for different age ranges: 6–11, the typical primary-school age range; 12–17, the corresponding age range for secondary education; and 18–24, the age range in which individuals are usually enrolled in tertiary education.⁶ On average, in 2020 there is a decrease in enrollment rates for all three age-groups. The strongest impact occurred among young adults aged 18–24 (almost 3 percentage points on average). However, in eight of the 12 countries in our sample, enrollment decreases substantially also in primary education. The lowest decline is found in secondary education.⁷ Tables A2 and A3 in the Appendix show the coefficient estimates separately by age groups for net enrollment and enrollment in private education, respectively. Interestingly, the decrease in private education enrollment is particularly strong at the tertiary education level (age range 18–24), which indeed is the educational level with the highest concentration of students enrolled at private institutions in most countries. Since we do not observe a significant increase in college graduation in 2020 with respect to previous years (see Figure A1 in the Appendix), we conclude that the drop in enrollment observed during the pandemic is driven by an increase in dropout.

⁶Baseline enrollment rates differ substantially across these age groups: 98% for children aged 6–11; 90% for children aged 12–17, and 46% for young adults aged 18–24.

⁷In very few countries, enrollment for some age groups slightly increases: in Argentina for children aged 6–11 by 0.5 percentage points; in Brazil and Costa Rica for children aged 12–17 by around one percentage point. However, there is no clear pattern for this increase across or within countries.

TABLE 2
THE LIKELIHOOD TO BE ENROLLED IN EDUCATION AND THE COVID-19 PANDEMIC

	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	MEX	PER	PRY	SLV
Panel A – Enrollment												
A2020	–0.0105* (0.00548)	–0.0114*** (0.00433)	–0.00430*** (0.00192)	–0.0536*** (0.00461)	–0.0142*** (0.00176)	–0.00107 (0.00496)	–0.0124*** (0.00433)	–0.000758 (0.00585)	–0.0141*** (0.00277)	–0.0493*** (0.00360)	–0.0108* (0.00633)	–0.00614 (0.00605)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average	0.81	0.86	0.78	0.80	0.77	0.81	0.79	0.80	0.76	0.78	0.79	0.72
Panel B – Net Enrollment												
A2020	–0.0135** (0.00572)	–0.0176*** (0.00404)	–0.0105*** (0.00218)	–0.0540*** (0.00465)	–0.0110*** (0.00178)	0.00575 (0.00547)	–0.0103** (0.00463)	–0.00667 (0.00627)	–0.00751** (0.00301)	–0.0446*** (0.00384)	–0.0184*** (0.00638)	–0.00994 (0.00633)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average	0.75	0.83	0.69	0.72	0.71	0.68	0.69	0.76	0.73	0.78	0.74	0.61
Panel C – Enrollment in Private Education												
A2020	–0.0228*** (0.00830)	0.0119*** (0.00437)	–0.0182*** (0.00268)		–0.0199*** (0.00216)	–0.0304*** (0.00521)	–0.00699 (0.00681)		–0.00782*** (0.00302)	–0.0327*** (0.00486)	–0.0321*** (0.00875)	–0.0115 (0.00796)
Controls	Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes	Yes
Average	0.29	0.11	0.21		0.19	0.14	0.27		0.11	0.24	0.24	0.20

Notes: The table summarizes the results of estimating Equation (3.1). The estimation sample includes individuals aged 6–24. Dependent variable indicated in the first row of the Panel. A2020 is a dummy for the year 2020. The point estimate shows the deviation in percentage points from the overall time trend in the dependent variable. Control variables include age, sex, urban or rural place of residence, and parental education. Average indicates the average value of the dependent variable over all years.

Source: National household surveys, 2009–2020. Own estimates.

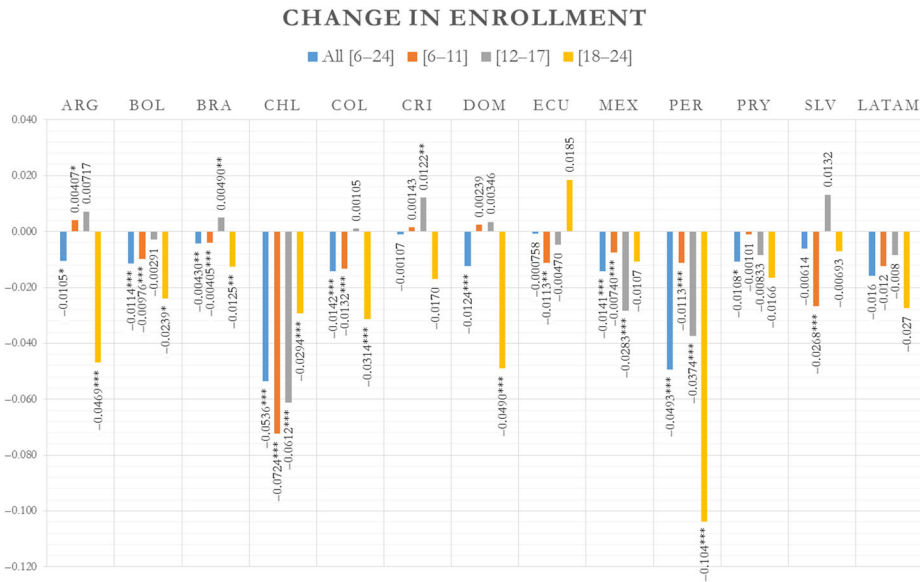


Figure 3. Change in Enrollment Rates in 2020 from Overall Time Trend by Age.
Notes: Values Attached to the Bars Indicate the Coefficient and its Statistical Significance. *Indicates that the Estimate is Statistically Significant at the 10% Significance Level. **Indicates that the Estimate is Statistically Significant at the 5% Significance Level. ***Indicates that the Estimate is Statistically Significant at the 1% Significance Level. A Coefficient of 0.01 Indicates a Change in Enrollment Rates—Conditional on Age, Sex, Parental Education and Rural/Urban Area of Residency—by One Percentage Point. The Last Four Bars (LATAM) Show the Unweighted Average of All Country-Coefficients.

Source: National Household Surveys, 2009–2020. Own Estimates

3.3. Change in Enrollment Across Subgroups

Figures A2–A4 in the Appendix show the effect of the pandemic on enrollment in Latin America for different population groups: men vs women; urban vs rural areas; low vs high parental education. For this analysis, we estimate Equation (3.1) for each group separately based on the pooled sample with normalized survey weights. In all cases, the estimates suggest a negative deviation from the trend in enrollment in 2020. However, in some cases, the effect of the pandemic on different sub-groups seems more heterogeneous. For instance, for households in rural areas we cannot reject that the change is not different from zero.

Enrollment rates in 2020 negatively deviate from the trend for both men and women. While the effect on enrollment and net enrollment is higher for men, the effect on enrollment in private education is higher, in relative terms, among women. However, these differences between genders are not statistically significant. A similar pattern emerges in the difference between urban and rural place of residence. The decrease in enrollment and net enrollment is sharper in urban areas, while not significantly different from zero in rural places. In contrast, the relative decrease in enrollment in private education is stronger in rural than in urban areas. In this case, the differences between groups are statistically significant.

We also assess heterogeneous effects on enrollment by parental education. We compare children of parents with a low level of education—that is, parents with a secondary education degree or less—and children of parents with a high level of education—that is, parents with more than a secondary education degree.⁸ In the two groups of children the decrease in enrollment (both gross and net) is similar, substantial, and statistically significant. Enrollment in private education is hereby an important exception: for this outcome, the relative decrease is stronger among the children of low-educated parents.

4. ESTIMATES OF EDUCATION LOSSES

In this section we follow the framework of Neidhöfer et al. (2021) (NLT thereafter) to approximate the educational loss associated with school closures. NLT nowcast the instructional losses associated to the pandemic using country level data on days of school closure, educational mitigation strategies, number of COVID-19 cases and deaths, and survey data on individual characteristics. The basic assumption is that the school closures in reaction to the pandemic affected the human capital accumulation through lost days of school. This loss could be compensated partly by parent's investments and actions, especially in more educated households, and partly by educational mitigation strategies enacted by countries.

In this section we extend the calculations of NLT by adding information from administrative data for 2021. More important, whereas the estimates in NLT are based on Latinobarometro, our calculations are based on microdata from national household surveys, which allows us (i) to have large samples, (ii) to include data at the household level on some key factors for the educational impact of COVID-19, such as parental education and access to internet, and (iii) to perform a rich analysis of heterogeneities, as national household surveys include information on income, wages and other relevant variables. The analysis based on national household surveys allows a more granular measure of the potential effect of the shock while also capturing asymmetries across population groups within countries.

4.1. *Methodology and Data*

School closures imply a severe interruption in the learning process, potentially leading to profound implications for the formation of both cognitive and non-cognitive skills in children, with subsequent effects on their future productivity and earnings. Furthermore, in line with Cunha and Heckman (2007) and Cunha et al. (2010), these effects would be highly asymmetric depending on the age of children and their family's socioeconomic level, thereby affecting long-term poverty and income inequality.

⁸In principle, the socioeconomic status of the family could also be approximated by household income. However, since this outcome is directly affected by the pandemic, the position of the household in the income distribution might not be a correct way of comparison over time. Hence, in this part of the analysis, we only evaluate differences by parental educational background, assuming that this measure is less likely to be affected by the pandemic (it would be so for younger parents, who are rather unlikely to have children in the age range from 6 to 24).

Unfortunately, it is extremely difficult to estimate the long run impact of the school closures due to COVID-19 on the human capital stock given the proximity of the shock and the data at hand. NLT provide first estimates on the long run effect of school closures based on two main simplifying assumptions: (i) the human capital stock, which is relevant as a determinant of future earnings, is well approximated by years of formal education, and (ii) the loss of human capital can be approximated by the share of the school year in which the learning process was interrupted. While the first assumption is standard in part of the literature (e.g., Black & Devereux, 2011), the second follows the contributions of Abadzie et al. (Abadzi, 2009) and Adda (2016).⁹ The human capital loss could be lower if successful compensating measures are taken in the future, but on the other hand, they could be larger if interruptions make the process of learning more difficult to resume and lead to cumulative learning losses over time.¹⁰

Following NLT, the loss of education (as a share of the school year) for individual i in country c is defined as:

$$(4.1) \quad k_{ic} = K_{ic} \cdot \alpha_{ic}$$

where K_{ic} is the share of instructional time lost in country c for student i , and α is a function of the parental factor of substitution, which takes into account that parents may compensate to a certain degree for the educational loss (see below). The instructional time loss is estimated as:

$$(4.2) \quad K_{ic} = \frac{t_c (1 - f_c \delta - n_c A_{ic} (1 - \delta)) + \tau_{ic}}{T_c}$$

where t is the number of days lost due to school closures in a given country and T is the number of school days in a regular year of schooling. The term in parenthesis is included to consider the compensation of schooling from public actions in home learning tools: f and n are indices that capture the extensiveness of offline and online education tools during the pandemic. f (n) equals one if all the offline (online) educational tools were used by the country's education system during the school closure, and zero if none of them was used. The parameter δ is a weight between the two sets of resources that defines their relative effectivity. Following NLT, we

⁹An argument against the first assumption would be that years of schooling do not capture differences in educational quality that lead to substantial differences in skill levels. Since we do not have information on cognitive abilities, we use only years of education here. As the estimates on the negative impact of the pandemic on enrollment in private education included in Section 3 suggest, not considering the quality of education makes our estimates to be a lower bound.

¹⁰Monroy-Gómez-Franco et al. (2022) provide an extension of the model that follows the framework of NLT and considers also cumulative learning losses. Their application to Mexican data indicates that a learning loss equivalent to one third of a school year could translate into a long-run learning loss between 1 and 2 years. Of course, there could be dynamic effects of the interruption in human capital accumulation. Disruptions earlier on in life may have longer lasting and more severe effects. This implies that younger children may be more heavily impacted than older ones.

initially set the weight δ equal to 0.5, meaning that both offline and online learning resources are equally capable to transmit learning material and may together be able to replace a regular day in class. Alternative values are used in the robustness analysis.

In NLT, A is defined as the likelihood to have access to the internet—a key factor to be able to receive on-line education—of students in households with a given educational background. In contrast to NLT, where this likelihood is predicted for each individual based on the distribution of access to the internet by education groups estimated for each country from other data sources, in our specification A is the actual availability of internet in the household, a piece of information available in most national household surveys.¹¹

The last term of Equation (4.2) captures the instructional loss due to health shocks. Formally,

$$(4.3) \quad \tau_{ic} = \tau^q \cdot P_{ic}(q = 1) + \tau^d \cdot P_{ic}(d = 1)$$

where q is infection of one of the household members with COVID-19, and d is death of a household member due to COVID-19. The probabilities $P(q = 1)$ and $P(d = 1)$ are estimated based on the number of COVID-19 infections and deaths per inhabitant in the country multiplied by the household size.¹² Parameters τ^q and τ^d are the respective days of schooling lost due to the occurrence of the two events. Like NLT we set τ^q to the average days of symptom duration (5 days of schooling), and τ^d to a three-week loss of instructional time (15 days).¹³

Finally, we assume that α in (4.1) is a decreasing function of parental education, which implies that more educated parents are better able to compensate for the educational loss of their children. There is recent evidence on the role of parental education in ameliorating the impact of educational losses during the pandemic, in line with our assumption in (4.4), which is crucial to determine the gradient for the educational losses (see e.g., Betthäuser et al., 2023; Moscoviz & Evans, 2022).¹⁴ For simplicity, we follow NLT in assuming a simple form for α :

$$(4.4) \quad \alpha_{ic} = 1 - \frac{e_{ic}}{\max_c(e)}$$

where e_{ic} measures parental educational background in the household of student i in country c and $\max(e)$ its maximum value in the sample (i.e., the years of education associated with tertiary education). Parental educational background is defined as the years of education of the parent in the household with the highest level of education.

¹¹Argentina and Ecuador are the only countries in our sample that do not have information on internet access. In these cases, we randomly imputed internet access based on the percentage of internet access by income deciles of similar countries (Uruguay and Peru, respectively).

¹²In this point we depart from NLT who take the average country-level household size and use data for 2020 to estimate the average household size for each country.

¹³The results are robust to changes in the number of days.

¹⁴We also carry out some robustness exercises assuming a constant α (see Section 5).

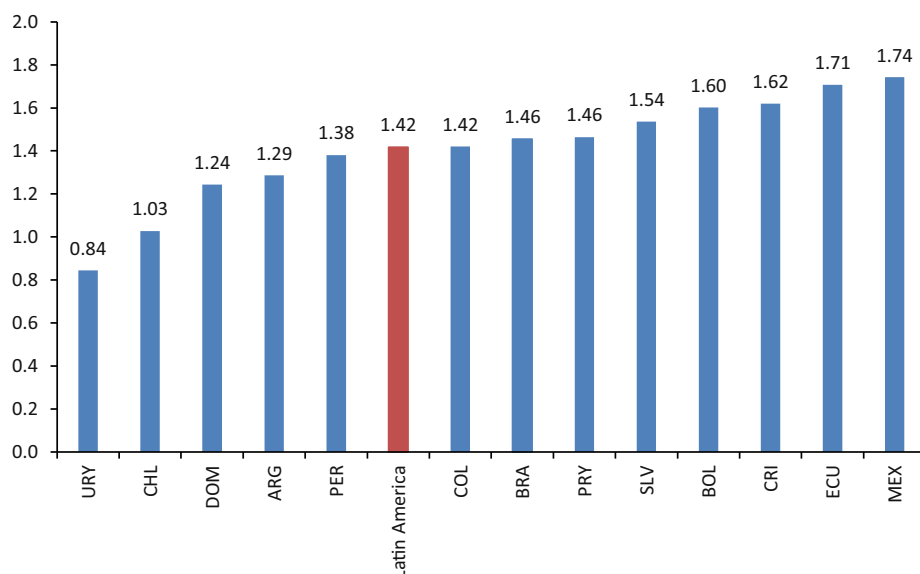


Figure 4. Days of School Closure in 2020–2021 (as Share of Days in a Typical Year).
Source: Own Calculations Based on Administrative Data.

4.2. Predicted Educational Losses

In this section we illustrate the results for the 12 Latin American countries analyzed in the previous section plus Uruguay.¹⁵ For the sake of simplicity, in most cases we present the unweighted cross-country average of the results—that is, we calculate the results for each country and then take the average across countries.¹⁶ The cross-country average represents the typical Latin American country, which we refer to as “Latin America.”

On average, schools in the region remained closed for a total of 269 days in 2020 and 2021 due to the COVID-19 pandemic. Considering that a standard school year in Latin America consists of 189 days, the cumulative school closures amounted to 1.42 years. The ratio of school closure days to the total number of days in a typical school year ranges from 0.84 in Uruguay to over 1.7 in Ecuador and Mexico (Figure 4).

Table 3 shows the summary statistics of k , that is, the share of a year of schooling lost due to the COVID-19 pandemic when adjusting for government and family reactions. The mean value for Latin America is 0.59: more than half of a year was lost due to the school closures even when considering compensatory measures.

¹⁵In Section 3 we analyze the 12 Latin American countries for which repeated cross-sections spanning the period 2010–2020 were available at the time of writing this paper. On the other hand, Sections 4 and 5 rely on data from a single year, making the data requirement less strict. This enables us to include an additional country (Uruguay) into the analysis in those sections.

¹⁶All main results are robust to the weighting decision.

TABLE 3
VALUES OF EDUCATIONAL LOSS BY GROUP, LATIN AMERICA

	Benchmark	With HFPS data
Mean	0.59	0.59
By parental education		
Low	0.82	0.81
Middle	0.43	0.45
High	0.14	0.13
By deciles of per capita income		
1	0.81	0.74
2	0.74	0.70
3	0.68	0.67
4	0.63	0.63
5	0.59	0.60
6	0.53	0.57
7	0.48	0.51
8	0.40	0.45
9	0.31	0.35
10	0.22	0.25
By area		
Rural	0.72	0.67
Urban	0.53	0.55
By gender		
Female	0.59	0.59
Male	0.59	0.59

Note: Unweighted mean of the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Mexico, Peru, Paraguay, and Uruguay.

Source: Own estimations based on the methodology developed by Neidhöfer et al. (2021), and microdata from national household surveys, and the three first rounds of the World Bank's High-Frequency Phone Survey (HFPS).

There is considerable heterogeneity across countries: from 0.32 in Uruguay to 0.85 in Ecuador (Figure 5).¹⁷

The value of k is not homogeneous as students differ in the access to internet, parental background, and household size. Table 3 reports the value of k by parental education and household per capita income deciles for the aggregate of Latin America. The education loss is strongly decreasing in the socioeconomic situation of the household. While the mean loss for a student in the bottom decile of the income distribution is estimated in 81% of a schooling year, the loss becomes 22 percent for a student in the top decile.¹⁸

¹⁷These results are largely in line with the initial projections for 2020 in Neidhöfer et al. (2021) and the updated projections in Lustig et al. (2021).

¹⁸As discussed above, these results are partly driven by our assumption of α decreasing in parental education. Table A4 reproduces Table 3 but assuming absence of parental compensation for educational losses ($\alpha = 1$). As expected, the values of k increase (from 0.59 to 0.82 for the Latin American mean). The negative relationship between educational losses and household income weakens but still persists. The mean loss goes from 94% of a schooling year for a student in the bottom decile of the income distribution to 64% for a student in the top decile.



Figure 5. Values of Educational Loss by Country.

Source: Own Estimations Based on the Methodology Developed by Neidhöfer et al. (2021) and Microdata from National Household Surveys.

4.3. Remote Learning with the World Bank's High-Frequency Phone Surveys

The World Bank's High-Frequency Phone Survey (HFPS) is one of the most ambitious data sets collected immediately after the onset of the pandemic. The surveys were carried out in over 100 countries, including 13 in Latin America. They offer real-time information on the situation and behavior of households during the first months of the pandemic, including information on remote learning strategies followed during school closures, such as online sessions and assigned homework.¹⁹

Using microdata from the first three rounds of these surveys—carried out between May and August 2020—, Bracco et al. (2022) show the estimated probability of children engaging in different remote learning activities by parental education. Unfortunately, due to the small samples, estimates are available only for the pool of Latin American countries.

In this section we use the estimated probabilities in Bracco et al. (2022) to help estimate instructional losses. Specifically, we compute k as:

$$(4.5) \quad k_{ic} = \frac{t_c (1 - \rho_i) + \tau_{ic}}{T_c} \cdot \alpha_{ic}$$

¹⁹Variables in the HFPS were harmonized by the World Bank, which helped foster a growing literature (Ballon et al., 2021; Cucagna & Romero, 2021; Khamis et al., 2021; Kugler et al., 2023; Mejia-Mantilla et al. 2021).

where ρ_i is the predicted probability of student i engaging in remote learning estimated with data from Bracco et al. (2022). Results are similar to the benchmark case discussed above (second column in Table 3). The educational loss is strongly decreasing in the socioeconomic status of the household. As expected, the gradients are somewhat smaller when using HFPS data, due to the higher degree of aggregation in the information we use for the calculations.

5. THE LONG-RUN IMPACT OF COVID-19 ON INCOMES, POVERTY, AND INEQUALITY

In this section we carry out microsimulations to provide rough estimates of the potential impact of the COVID-19 pandemic on future incomes and indicators of poverty and inequality through the educational channels discussed in previous sections. The exercises are necessarily based on several restricting assumptions and hence should be taken only as informed back-of-the-envelope calculations, aimed at informing the public debate on this very relevant issue.

5.1. Methodology

We start from an income distribution in baseline year t_o . We choose 2019, the most recent year with available microdata from a national household survey for most countries. Data for 2021 were not yet available for most countries at the time of writing this paper, and 2020 was a very unusual year to use it as baseline.

For simplicity, and to focus only on the impact of the pandemic through the educational channel, we assume that without the COVID-19 pandemic the educational structure and income distribution T years after t_o (t_T) would be identical to those in the baseline year. For simplicity in the explanation, we focus on year 2045, that is, 25 years after the COVID-19 shock. In Section 5.3 we extend the analysis to the dynamics of the impact over time. Also, in the interest of simplicity, we initially assume that the pandemic in 2020 affected human capital accumulation of children and youths aged 5–20. Consequently, in year 2045 the workers who were affected by the pandemic back in 2020 are those aged 30–45. This will be our “treatment group” G .²⁰

The key step of the methodology consists in changing the years of education of each person i in country c belonging to group G and simulating her labor income x_{ic}^V . In particular, we subtract k_{ic} years (or fraction of a year) of education lost due to the COVID-19 pandemic to each adult in group G with positive earnings and simulate her income based on a Mincer equation. The simulated income for worker i , x_{ic}^V , is obtained from the following expression:

$$(5.1) \quad \ln x_{ic}^V = \hat{\beta}_c^0 (e_{ic}^0 - k_{ic}) + \hat{\gamma}_c^0 X_{ic}^0 + \hat{\varepsilon}_{ic}^0$$

where e^0 is years of education, and X^0 are other variables observed in t_o (and assumed to be the same in T). β^0 and γ^0 are parameters estimated with t_o data and

²⁰This approach is similar to one that assesses the counterfactual impact on the current generation of adults of a hypothetical COVID-19 shock occurred 25 years ago.

the last term is the estimated error that captures unobserved factors. Importantly, (5.1) implicitly assumes that the parameters do not change after a change in the distribution of education.

According to the discussion in previous sections, we carry out two simulations: (1) we subtract months of instructional loss to all adults in G due to school closures, following the methodology explained in Section 4, and (2) we subtract years of education to dropouts associated to the pandemic according to the results in Section 3.

Months of Instructional Loss

In this case, k_{ic} in Equation (5.1) is the loss of education for individual i in country c estimated following an updated version of the Neidhöfer et al. (2021) methodology detailed in the previous section. There is, however, a relevant difference between the analysis in Section 4 and the input we need for the microsimulations. In the previous section we compute k for children and youths in 2019 for whom we observe the actual access to internet A and estimate the parental factor of substitution α with information about the actual parental background. The nature of the simulation in this section is different. We are pretending we are in 2045, so for instance A_{ic} should be the access to internet in 2020 of those adults in 2045 who were students during the pandemic.²¹

Given this limitation, we proceed by combining two extreme assumptions on intergenerational mobility. First, we assume zero intergenerational mobility, which implies that, first, children have the same level of education as their parents and, second, that internet access in childhood can be approximated by the current availability of internet in the household where adult i lives. The other alternative extreme assumption is of perfect mobility. In that case we randomly assign internet access to each adult in a way that is consistent with the overall internet coverage among the population, and also randomly impute parental education, independent of their own level of education.

Finally, we combine these two extreme alternatives to obtain our estimates. Weights for the two alternatives are assigned based on country intergenerational mobility estimates provided by Neidhöfer et al. (2018). In particular, we take the typical measure of intergenerational mobility of education, which arises from a regression of children's education on their parents' education. The lower the mobility in education, the higher the weight we assign to the scenario of zero mobility described above.²²

²¹Since retrospective questions are not included in most household surveys at our disposal, we do not know the parental background of these adults. Anyway, it is not clear that retrospective questions would be very helpful. For instance, retrospective questions on access to internet in childhood would be senseless for adults in 2019 who were children in the late 1980s, when internet was unknown for most people.

²²For instance, the intergenerational educational mobility measure based on regressing children's education on parental education estimated by Neidhöfer et al. (2018) in Peru is 0.51. This is, in fact, a measure of *persistence*, so in our simulations we assign the weight 0.51 to the zero-mobility case and the complement (0.49) to the perfect mobility case. For robustness, we also (i) consider the correlation coefficient as a measure of persistence rather than the regression coefficient, and (ii) alternatively use intergenerational mobility parameters estimated with Latinobarometro and national household surveys

Dropouts

As discussed in Section 2, the COVID-19 pandemic had a more dramatic effect on young people that go beyond the interruption of classes during several months: it may have implied even a dropout from the education system. We adopt the following strategy to measure the effect of this factor. As above, we assume that without the pandemic the educational structure in the future (2045) will be that of the baseline year t_0 . The pandemic implied a shock on this structure since some of the students dropped out of school. In our baseline scenario we assume that the increase in dropouts between 2019 and 2020 was permanent: students who dropped out do not return to the education system. We use the estimates in Section 4 on increases in dropouts by age group. For simplicity, the treatment population G is divided into three groups: $g_1 = [30-37]$, $g_2 = [38-42]$, $g_3 = [43-45]$. The adults in group g_2 in 2045, for instance, are those aged 13–17 during the pandemic shock in 2020.

We make a conservative assumption in order to select the dropouts in each age group of adult workers: students who dropped out of school at a given age due to the COVID-19 shock are those less likely to have advanced much in their educational paths without the shock. So, for instance, we assume that dropouts in group g_2 , who were 13–17 in 2020 and hence who dropped out of high school during the pandemic, would have ended with at most incomplete tertiary education but not more. Once we randomly select the dropouts considering the above assumption, we compute the loss of years of education k due to the drop out of individual i in country c as,

$$k_{ic} = e_{ic} - ((\text{age}_{ic} - 25) - EA_c)$$

where e is years of education and EA_c is the typical age to start formal education in country c . Take for instance a young adult aged 35 with 11 years of formal education. This person was 10 years old in 2020 during the shock, so if $EA = 6$ in that country, in principle he had 4 years of education at that moment. If (in the simulation) she dropped out of school due to the pandemic, she lost 7 years of education.

5.2. Results

The average results for Latin America are presented in Table 4. For each simulation the table shows average labor income (in PPP USD),²³ average household per capita income (in PPP USD), the Gini coefficient for the distribution of per capita income, and three poverty measures computed using the 6.85-USD-a-day line: the poverty headcount ratio, the poverty gap and the severity index (FGT(2)). In most panels there are three sets of indicators computed for (i) the group of dropouts, (ii) the cohort aged 30–45 in the base year, and (iii) the whole population.

The first column (“original”) shows values for 2045 without the COVID-19 shock, which, by construction, are those for the year of the latest available household survey (2019). The second column displays the results for the drop-out exercise. Since we randomly select the dropouts (within the groups), in column (ii) we show

microdata, both provided in the original study by Neidhöfer et al. (2018). Our results are robust to all different specifications.

²³2017 PPP computed in the framework of the International Comparison Program (ICP).

TABLE 4
THE IMPACT OF COVID-19 ON INCOME, POVERTY AND INEQUALITY: LATIN AMERICA. ESTIMATES FOR YEAR 2045

	Proportional changes													
	Instructional loss				Combined effects				Instructional loss				Combined effects	
	Original (i)	Dropouts (ii)	No adjustment (iii)	Full adjustment (iv)	No adjustment (v)	Full adjustment (vi)	Dropouts (vii)	No adjustment (viii)	Full adjustment (ix)	No adjustment (x)	Full adjustment (ix)			
Mean labor income														
Group of dropouts	523	431			431	431	-17.6%			-17.6%		-17.6%		
Cohort 30–45	1048	1048	891	999	890	999	-0.1%	-15.0%	-4.7%	-15.1%	-4.7%	-4.7%		
All workers	940	940	880	921	880	921	0.0%	-6.4%	-2.0%	-6.4%	-2.0%	-2.0%		
Mean per capita income														
Group of dropouts	231	210			210	210	-9.0%			-9.0%		-9.0%		
Cohort 30–45	700	700	627	678	627	678	0.0%	-10.5%	-3.2%	-10.5%	-3.2%	-3.2%		
All individuals	597	597	571	589	571	589	0.0%	-4.3%	-1.4%	-4.4%	-1.4%	-1.4%		
Inequality – Gini coefficient														
Cohort 30–45 (labor income)	0.422	0.422	0.411	0.422	0.411	0.423	0.1%	-2.5%	0.2%	-2.4%	0.2%	0.3%		
All individuals (p/c income)	0.448	0.448	0.447	0.448	0.447	0.448	0.0%	-0.2%	0.1%	-0.2%	0.1%	0.2%		
Poverty – Incidence														
Group of dropouts	44.2	54.3			54.3	54.3	22.7%			22.7%		22.7%		
Cohort 30–45	14.2	14.3	16.9	15.3	17.0	15.4	0.6%	19.3%	7.9%	19.6%	8.4%	8.4%		
All individuals	20.4	20.5	22.0	21.1	22.1	21.1	0.2%	7.9%	3.2%	8.0%	3.4%	3.4%		
Poverty – Gap														
Group of dropouts	12.8	17.1			17.1	17.1	33.5%			33.5%		33.5%		
Cohort 30–45	4.4	4.4	5.3	4.8	5.3	4.8	0.8%	20.2%	8.4%	20.6%	9.0%	9.0%		
All individuals	7.1	7.1	7.6	7.3	7.6	7.3	0.3%	8.0%	3.4%	8.1%	3.6%	3.6%		
Poverty – Severity														
Group of dropouts	5.6	7.8			7.8	7.8	38.5%			38.5%		38.5%		
Cohort 30–45	2.0	2.1	2.4	2.2	2.5	2.2	0.8%	20.2%	8.6%	20.7%	9.3%	9.3%		
All individuals	3.6	3.6	3.8	3.7	3.8	3.7	0.3%	7.7%	3.3%	7.8%	3.6%	3.6%		

Notes: Original: values for 2045 assuming no changes from 2019 to 2045. No adjustment: values assuming no government or parental reactions to loss of days of school during the pandemic. Only parental reaction: values assuming only parental reactions to loss of days of school during the pandemic. Full adjustment: values assuming both government and parental reactions to loss of days of school during the pandemic. Unweighted mean of the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Mexico, Peru, Paraguay, and Uruguay.

Source: Own estimations based on microdata from national household surveys.

the mean results over 50 draws. The next two columns show the results for the exercise of instructional losses due to school closures under two extreme alternatives: assuming no adjustments to the loss of days of school ($f=n=0$ and $\alpha = 1$), and assuming parental and government adjustments (f and $n > 0$, and $\alpha < 1$). Columns (v) and (vi) present the combined effects of the two exercises (dropouts and school closures). The second panel of the table—columns vii to xi—shows proportional changes in relation to the original situation for each indicator.²⁴

The impact of leaving school is strong over the group of dropouts. Mean income falls by 17.6 percent, the incidence of poverty climbs by 22.7 percent and the severity of poverty jumps by 38.5 percent. Since the proportion of dropouts is relatively small (around 1 percent) the size of the impact becomes small for the treated cohort 30–45, and tiny for the whole population. The poverty headcount ratio increases by 0.6 percent in the cohort 30–45 and by 0.2 percent in the population due to the drop-out effect.

The impacts are larger due to the generalized instructional losses caused by the school closures. If reactions to school closures were inexistent or fully ineffective (columns iii and viii), the COVID-19 shock would imply a fall by around 15 percent in earnings in the treatment group in 2045. The impact would be a decline by 10.5 percent of average household per capita income. These income changes have significant effects over the poverty indicators within this group: the poverty headcount ratio would increase by 19.3 percent, the poverty gap by 20.2 percent and the severity index by 20.2 percent. Values are smaller (around 8 percent) when considering the impact on the entire population.

Interestingly, the Gini on the distribution of labor income for the treated group *decreases*. This is not an unexpected result. It is driven by the combination of (i) the subtraction of a similar number of days of schooling to all individuals, and (ii) the convexity of the earnings-education profile. This fall in inequality is the other side of the “paradox of progress” (Alejo et al., 2022; Bourguignon et al., 2004). Unlike inequality in labor income, the Gini for the distribution of household per capita income remains roughly unchanged, likely due to a compensating factor: labor income is a less important source of income in the top of the distribution than in the bottom, due to the role of capital income.

Column (iv) reveals that the government and parental reactions could have had a partial ameliorating effect on the impact of the COVID-19 shock. For instance, the poverty gap in the treated group increases only by 8.4 percent instead of 20.2 percent if both government and parents effectively reacted to the school closures. Consistent with the fact that reactions to school closures were asymmetric across households depending on the socioeconomic status, we find a (very minor) increase in inequality in the full adjustment alternative, over both the labor and the per capita income distributions.

The last columns in the table show the combined effects. The COVID-19 pandemic implies a substantial increase in poverty among school dropouts (between

²⁴Table A5 in the Online Appendix reproduces Table 6 assuming absence of parental compensation ($\alpha = 1$) in all columns. As expected, the results are intermediate between the scenarios of no adjustment and full adjustment with $\alpha < 1$.

22.7 percent and 38.5 percent depending on the indicator). For the treated cohort 30–45 and for the entire population the results are mostly driven by the instructional losses due to the school closures. Poverty would increase between 8.4 percent and 20.7 percent in the shocked cohort, depending on the indicator and on the effectiveness of the reactions of governments and families during the pandemic to compensate for the school closures. The increase in income poverty for the entire population would be in the range between 3.4 percent and 8.1 percent. The sign of the changes in income inequality depends on the parental adjustments: unequalizing with full adjustment and equalizing with no adjustments. In any case, changes in income inequality would be almost negligible.²⁵

5.3. Dynamics

The previous exercises were focused on a particular year in the future (2045), when all the students in 2020 are already young adults. In this section we extend the analysis to the period 2021–2075 and examine the dynamics of the impact. The main results are presented in Figures 6–8. The figures show the trajectories over time of household per capita income, inequality, and poverty after the COVID-19 shock on education under two alternative assumptions: no adjustment and full adjustment by families and government.

Figure 6 reveals an initial larger drop in income in 2021 after the shock, as a result of the loss in human capital for the group of young workers affected by the pandemic. This group is, however, small since in 2021 individuals in the treatment group are aged 6–21, and hence few of them are active in the labor market. The impact of the shock on education during the pandemic grows over time as the treatment cohort becomes older and enters the labor market. However, at some point this generation starts to retire and then the effect vanishes away.²⁶ The impact of the COVID-19 shock on incomes would reach its maximum value in 2045. Figure 7 shows similar patterns for two income poverty indicators: the headcount ratio (panel a) and the severity index (panel b).

The dynamics in the case of inequality are rather different (Figure 8). Initially, as the shock affects young workers, who are typically poorer than the rest, the impact is unequalizing. As times passes the treatment group becomes older and more affluent, and then the COVID-19 shock turns equalizing. In any case, changes are very small, and become even smaller in the case of full adjustment.

5.4. Comparison with Fuchs-Schündeln et al. (2022)

As explained above, to obtain these estimates we employed microsimulations and mainly relied on the approach developed by Neidhöfer et al. (2021) (NLT) to simulate the impact of the pandemic on educational attainments. A complementary

²⁵The effects on inequality could be substantially larger than our estimates due to other channels, such as significant asymmetries in educational quality during the pandemic or in the speed of the recovery of the learning process after the shock (Kaffenberger, 2021; Monroy-Gómez-Franco, 2022).

²⁶Here, we are ignoring the potential effect of the shock on the intergenerational transmission of human capital. Children of the cohort that suffered the COVID-19 pandemic may also be affected through lower human capital accumulation of their parents.

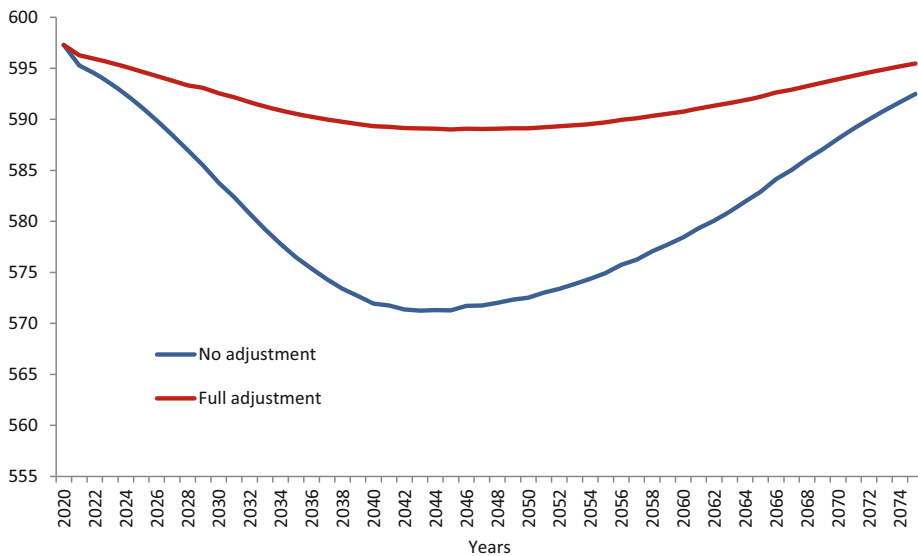


Figure 6. Pattern of Household Per Capita Income Over Time After the COVID-19 Shock on Education. Latin America.

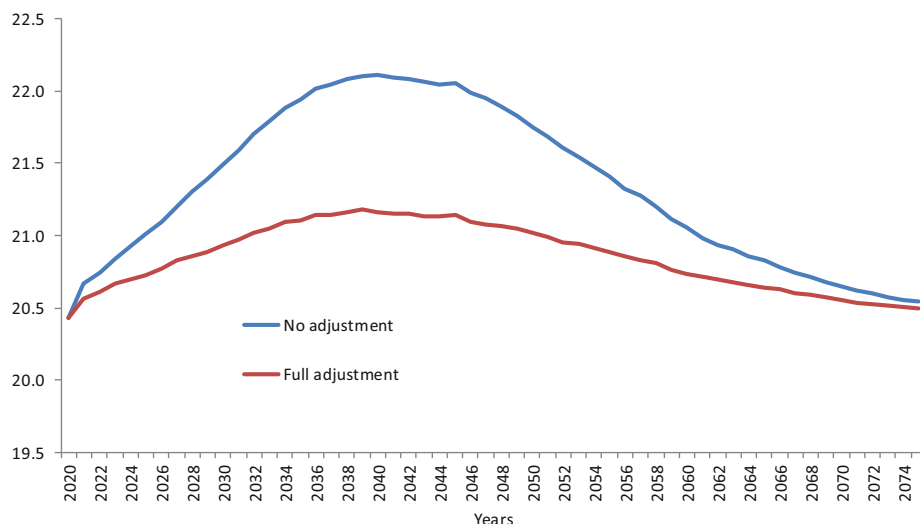
Source: Own Estimations Based on Microdata from National Household Surveys

Note 1 No Adjustment: Values Assuming no Government or Parental Reactions to Loss of Days of School During the Pandemic. Full Adjustment: Values Assuming Both Government and Parental Reactions to Loss of Days of School During the Pandemic. Note 2 Values in Monthly 2017 PPP Dollars. Note 3 Unweighted Mean of the Following Countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador Mexico, Peru, Paraguay, and Uruguay.

analysis that estimates the long-term distributional impact of COVID-19 school closures is Fuchs-Schündeln et al. (2022) (FKLP), who employ a structural life-cycle model and calibrate their model using US data. Similar to our analysis and NLT, they consider two main inputs: parental and governmental investment in education. While we capture parental investments through their correlation with parental education without specifying different channels, FKLP consider monetary investment and time investment separately in the model. They show that both monetary and time investment are positively correlated with parental education. Another difference between the two approaches is that FKLP consider differential effects of school closures at different ages by incorporating dynamic complementarities in human capital production, while NLT assume that the strength of the impact does not vary with age and show, by robustness checks, that the results are not sensitive to this assumption.

FKLP initially assume school closures of 1 year and additionally analyse the effects of remote learning as a mitigation measure, assuming that it is able to mitigate half a year of schooling loss. Following NLT, we instead measure the length of school closures and compensatory measures empirically for each country in the sample based on various indicators and data sources. However, the results from both studies show a similar pattern: substantial long-term implications for affected children, with a stronger impact on disadvantaged children. FKLP highlight that

(a) Headcount ratio



(b) Severity index

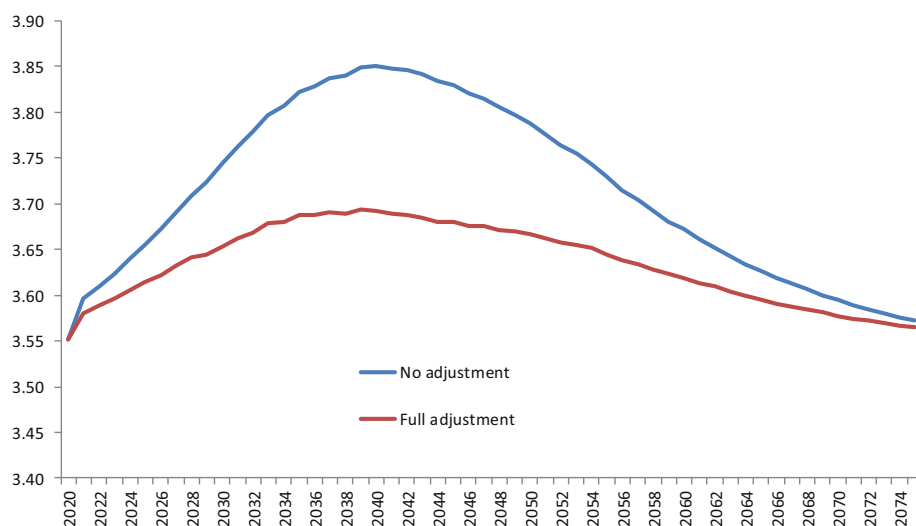


Figure 7. Pattern of Poverty Over Time After the COVID-19 Shock on Education. Latin America.

Source: Own Estimations based on Microdata from National Household Surveys.

Note 1 No Adjustment: Values Assuming no Government or Parental Reactions to Loss of Days of School During the Pandemic. Full Adjustment: Values Assuming Both Government and Parental Reactions to Loss of Days of School During the Pandemic. Note 2 Poverty Line of 6.85 Dollars a Day at 2017 PPP. Note 3: Unweighted Mean of the Following Countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Mexico, Peru, Paraguay, and Uruguay.

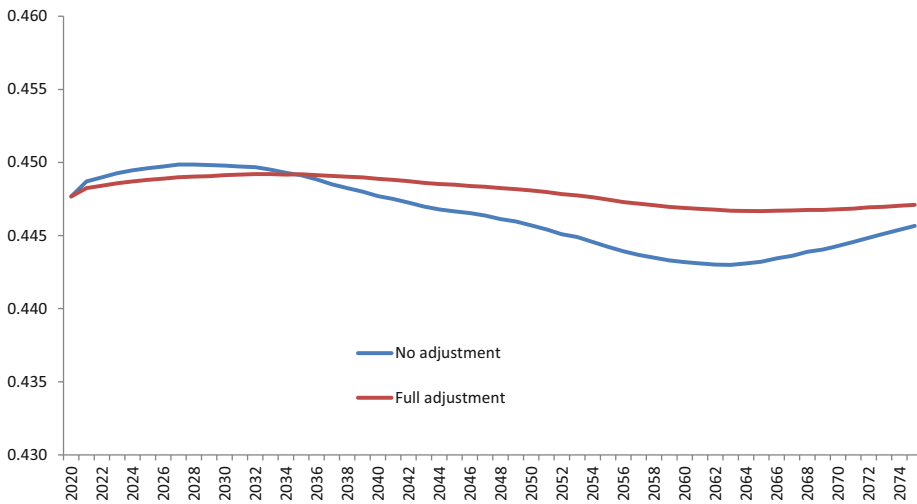


Figure 8. Pattern of Inequality (Gini Coefficient) Over Time After the COVID-19 Shock on Education. Latin America.

Source: Own Estimations based on Microdata from National Household Surveys.

Note 1 No Adjustment: Values Assuming no Government or Parental Reactions to Loss of Days of School During the Pandemic. Full Adjustment: Values Assuming Both Government and Parental Reactions to Loss of Days of School During the Pandemic. Note 2 Unweighted Mean of the Following Countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Mexico, Peru, Paraguay, and Uruguay.

all children leave the pandemic with reduced human capital, while in the approach of NLT highly educated parents completely substitute schooling during closures, which seems consistent with existing empirical evidence of minimal impacts on children of highly educated parents (e.g., Betthäuser et al., 2023). In other estimations, FKLP also assume perfect substitutability between parents and schooling, leading to weaker average long-run welfare losses but stronger distributional effects. In conclusion, although the models and methodologies employed in this paper and in FKLP differ, the main assumptions and findings on the long-run impacts of COVID-19 school closures are generally consistent.

6. CONCLUDING REMARKS

As part of national strategies to contain the spread of the COVID-19 disease, schools were temporarily closed. The interruption was not minor: on average in Latin America schools remained closed for almost one and a half years. There is great concern over the future economic cost of these closures (Hanushek & Woessmann, 2020; Psacharopoulos et al., 2020). On the one hand, the crisis implied an increase in dropout rates, and, therefore, a dramatic break in the human capital formation of many young people. But the disruption was also costly for those who did not drop out. The dynamic nature of skill acquisition implies that learning interruptions are difficult to compensate, and that the effects largely depend on the age of children and their family socioeconomic background (Cunha et al., 2010; Cunha &

Heckman, 2007). Many of the children and young people affected by the pandemic are likely to enter adult life with fewer skills than they would have otherwise, and consequently they will have lower expected lifetime earnings. Moreover, the school closures have magnified the influence of parental characteristics on the education received by their children.

In this paper we document that despite efforts by national education systems and families to provide learning options, the process of human capital accumulation of children and youths was severely affected in Latin America. Some children and youths dropped out of school, and those who remained had to adapt to a new learning environment. Our results show that enrollment rates and enrollment in private education were significantly lower in 2020 than in previous years. The losses were large and asymmetric: children from disadvantaged families were more likely to drop out of school and less likely to be enrolled in private education. This indicates that the pandemic had a considerable short-time effect on educational investments.

The disruption in human capital formation is likely to have long-run consequences on earnings, and hence on poverty and inequality. We provide some rough estimates of this effect by carrying out microsimulations for most Latin American countries. We find that the COVID-19 pandemic may imply a substantial increase in income poverty in the future for the shocked cohort: between 8.4 percent and 20.7 percent, depending on the indicator and on the effectiveness of the reactions of governments and families during the pandemic to compensate for the school closures. The impact would be harsher for those who dropped out of school: an increase in poverty between 22.7 percent and 38.5 percent depending on the indicator.

Altogether, these results provide evidence consistent with a relevant policy lesson highlighted in other studies (e.g., Ballon et al., 2021): stringent lockdowns and closures helped to save lives but at the same time led to substantial welfare losses, a fact that should be seriously taken into account in the design of the optimal policy responses to this type of shock, and in the implementation of compensatory measures in the years to come. Therefore, it is crucial to implement evidence-based strategies that can mitigate the long-term effects of the pandemic on education.

To address the educational losses caused by the pandemic, various measures can be implemented (see e.g., the summary by Lustig et al., 2021). These include compensating for lost instructional time and content, as loss of instructional time has a negative impact on educational outcomes and may affect future life earnings (e.g., Almond, 2006). Specific recommendations include extending school days (Cerna et al., 2020; UNESCO, 2020b; World Bank, 2021) and targeted learning for challenged students (UNESCO, 2020a). High-quality tutoring initiatives, especially for students from disadvantaged backgrounds, can also be effective in addressing learning gaps (e.g., De Ree et al., 2023). Additionally, offering mentoring programs to students, particularly those from disadvantaged backgrounds, can alleviate the negative effects of family disadvantages (e.g., Resnjanskij et al., 2021). Hereby, increasing dialog between families and schools can foster participation in educational activities (UNESCO, 2020b). Finally, focusing on the right margins is necessary. Prioritizing the presence of at-risk students in school, offering solutions that guarantee learning continuity, and targeting vulnerable students can help mitigate the unequalizing effects of school closures and their long-term impact.

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